PadhAI: Representation Power of Functions

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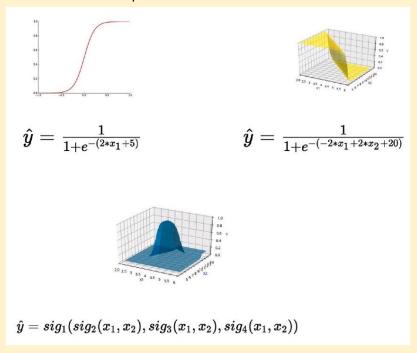
Why do we need complex functions

The need for complex functions

1. Here's a quick recap on what we've covered so far

	Data	Task	Model	Loss	Learning	Evaluation
MP Neuron	{0,1}	Binary Classification	$g(x) = \sum_{i=1}^{n} x_i$ $y = 1 \text{ if } g(x) >= b$ $y = 0 \text{ otherwise}$	Loss = $\Sigma_i(y_i!=\widehat{y}_i)$	Brute Force Search	Accuracy
Perceptron	Real Inputs	Binary Classification	$y = 1$ if $\sum_{i=1}^{n} W_i X_i >=$ b y = 0 otherwise	Loss = $\sum_{i} (y_i - \hat{y}_i)^2$	Perceptron Learning Algorithm	Accuracy
Sigmoid	Real Inputs	Classification /Regression	$y = \frac{1}{1 + e^{-(w^T x + b)}}$	$\begin{aligned} & \text{Loss} = \sum_{i} (\mathbf{y}_{i} - \widehat{\mathbf{y}}_{i})^{2} \\ & \text{Or} \\ & \text{Loss} = \\ & - [(1 - y)log(1 - \widehat{\mathbf{y}}) + ylog(\widehat{\mathbf{y}})] \end{aligned}$	Gradient Descent	Accuracy/RMSE

- 2. We must remember that none of the above 3 models can handle non-linearly separable data
- 3. Here's another recap on Continuous Functions

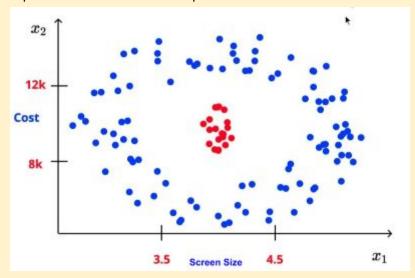


- 4. We care about continuous functions because our learning algorithm (Gradient Descent) requires that the input functions be differentiable (i.e. Continuous)
- 5. Let's take a look at a real world example of how complex functions are relevant to our situation

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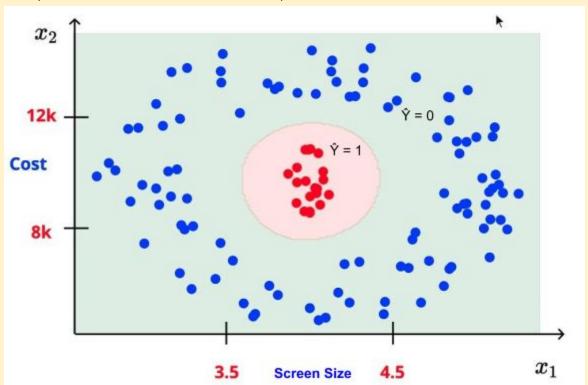
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6. Consider the following example of where we're trying to predict like/dislike for a non-linearly separable dataset of mobile phones.



- 8. Here, our desirable set of phones lies in the centre of a circle of non-desirable phones, based on the values of the variable Cost and Screen Size.
- 9. Ideally, we would need a decision boundary like so

7.



10. However, none of the functions we have seen so far will be able to plot such a decision boundary (ie boundary that separates the two classes = 0 and \hat{y} = 1)

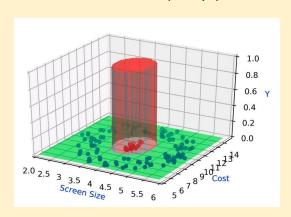
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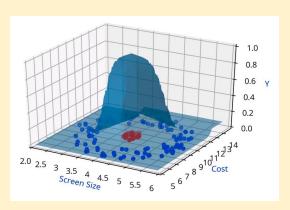
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11. Let's take a 3D plot of the two variables with the output values mapped along the z-axis

Discrete (abrupt)

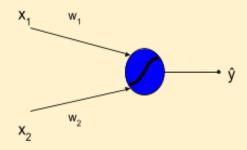
Continuous (smooth)

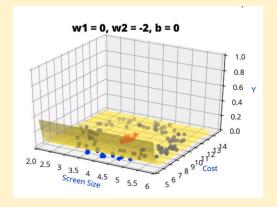


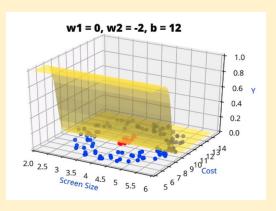


- 12. Here, the Continuous function has a smooth distribution, and the Y value gradually increases as we converge to the centre, becoming 1 at the region around the red dots
- 13. However, such an output is not possible with the sigmoid functions, regardless of how we manipulate the values of w and b

Sigmoid decision boundary, can range from s-shape to flat, based on w and b values







- 14. We can see that the sigmoid function is unsuitable for modelling complex decision boundaries.
- 15. Such complex relations are actually seen quite frequently in real world examples